Implied Risk Exposures

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Abstract

We show how to reverse-engineer banks' risk disclosures, such as Value-at-Risk, to obtain an implied measure of their exposures to equity, interest rate, foreign exchange, and commodity risks. Factor Implied Risk Exposures (FIRE) are obtained by breaking down a change in risk disclosure into a market volatility component and a bank-specific risk exposure component. In a study of large US and international banks, we show that (1) changes in risk exposures are negatively correlated with market volatility and (2) changes in risk exposures are positively correlated across banks, which is consistent with banks exhibiting commonality in trading.

Keywords: Risk Disclosure, (Stressed) Value-at-Risk, Regulatory Capital, Systemic Risk

JEL Classification: G21, G28, G32

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1 Introduction

There are many reasons for financial institutions to have correlated risk exposures. First, capital regulations around the world incentivize banks to over-invest in certain favorable asset classes, such as sovereign debt. Second, banks may share superior information, and as such, follow similar investment strategies (Hirshleifer, Subrahmanyam, and Titman, 1994). Third, banks have incentives to herd to maximize the likelihood of being bailed out (Acharya and Yorulmazer, 2007, 2008; Farhi and Tirole, 2012).

Correlated risks are especially problematic during financial crises. Indeed, as market volatility spikes, regulatory capital and collateral requirements tend to mechanically increase for financial institutions. In response many banks are forced to liquidate their positions, which further amplifies market volatility (Brunnermeier and Pedersen, 2009; Merrill et al., 2013). The resulting adverse feedback effects are stronger when banks have correlated risk exposures as they tend to sell the same assets at the same time (Morris and Shin, 1999; Persaud, 2000).

A traditional approach to measuring banks' risk exposures is to regress the banks' stock returns on potential risk factors (Flannery and James, 1984; Bhattacharyya and Purnanandam, 2011). Alternatively, O'Brien and Berkowitz (2006) regress the daily trading revenues of six US banks on the ten-year US Treasury rate and other market risk factors. They find that US banks exhibit high level of heterogeneity in their risk exposures, except for interest rates. More recently, some new approaches have been proposed to infer banks' exposures to interest rate risk from accounting data. Begenau, Piazzesi and Schneider (2013) use a portfolio approach to measuring banks' exposures to interest rate risk from data on loans and interest rate swaps. They show that derivatives increase banks' exposure to interest rate risk. Landier, Sraer and

Thesmar (2013) show that the interest rate sensitivity of US banks' profit increases with their income gap, which is defined as the difference between assets and liabilities that mature in less than one year.

This paper proposes a new and simple way to measure risk exposures. Unlike previous papers, we do not focus on interest rate risk and consider a broader spectrum of risks, namely equity risk, interest rate risk, foreign exchange (FX) risk, and commodity price risk. Furthermore, we extract implied risk exposures of banks from their *public risk disclosures*, with special emphasis on Value-at-Risk (VaR).[1] We exploit the fact that the level of risk disclosures depends on two main factors. It first reflects current market conditions and as such, tends to rise with market volatility. A second driving force of a bank's risk disclosure, but one that is often hidden to the public eye, is the actual risk exposures of the bank. Indeed, taking over a major stock broker would lead to a higher equity VaR for the acquiring bank. Similarly, implementing a directional trading strategy on the commodity market would certainly inflate the commodity risk figures.

We show how to decompose a change in risk disclosure into a market volatility component and a bank-specific risk exposure component. The trick we use is straightforward, yet powerful. For a broad family of distributions, the VaR is defined as the product of the standard deviation of the return and the dollar amount invested (up to a constant scaling factor). Consequently, the change in VaR can either be due to a change in volatility or in the amount invested, or both. As the former two pieces of information are public information, they can be used to extract an implied measure of the latter. This framework, which we dub "Factor Implied

[1] The VaR corresponds to a loss that should only be exceeded with a given target probability over a given time horizon (Jorion, 2007). We show in Section 4.1 that our methodology can also be implemented with other types of risk disclosures.

Risk Exposure" or FIRE, allows us to answer two important questions: (1) How do banks adjust their risk exposures in response to volatility shocks? (2) Are changes in risk exposures correlated across banks? In other words, we investigate whether banks exhibit commonality in trading and whether correlation in risk exposures strengthens when financial markets are under stress.

We assess the performance of the FIRE in an innovative way. For a large financial institution, we systematically compare the implied risk exposures given by the FIRE with statements made by the firm about its actual risk exposures in public filings. Using quarterly data between 2003Q1 and 2013Q3, we have not found a single occasion in which the estimated risk exposures and the stated risk exposures contradict each other. We believe that this is reassuring evidence that our method provides meaningful risk estimates. We also study by simulation the biases on the implied exposures that could be induced by model risk and estimation risk. Overall, we find that the bias in the exposures is relatively small whatever the experiment and the sample size considered.

To develop the intuition underlying our approach, we display in Table 1 the changes in VaR for ten large US and international banks during an episode of substantial reduction in volatility (2008Q4-2009Q4). The VaR figures have been computed by the banks with a 99% confidence level and a one-day horizon. One attractive feature of this dataset is that it includes risk figures (factor VaR) that are defined separately for each source of risk: equity, interest rate, FX, and commodity price. During this period, volatility fell across all asset classes. The actual reduction in volatility was 46% in the equity market, 43% in the fixed-income market, 39% in the FX market, and 59% in the commodity market.[2] Despite the overall drop in

[2] We use a specific volatility index for each risk factor (see caption of Table 1 for more details).

volatility, we identify 17 cases, out of 40, in which the VaR *increased* over the same period. One potential explanation of this puzzling result is that volatility (↓) and risk exposures (↑) moved in opposite directions and that the risk exposure effect dominated the volatility effect for some banks.

< Insert Table 1 >

In the empirical part of the paper, we use quarterly VaR data publicly disclosed by the same ten US and international banks between 2007 and 2013. We use separate VaR figures for each major source of risk: equity, interest rate, FX, and commodity. To control for concurrent changes in volatility, we use several proxies including implied volatility and historical volatility. Our empirical analysis leads to several new findings on the risk-taking behavior of banks. First, we find that VaR covaries more frequently and more strongly with risk exposures than with market volatility. This result contrasts with the abundant literature on VaR computation in which attention is made on forecasting volatility models as the portfolios' weights are assumed to be constant. We show in this paper that when we allow for time-variation in the risk exposures, we end up with a much richer VaR dynamics. Second, we show that changes in risk exposures are negatively correlated with volatility changes, which suggests that banks curb risk when financial markets are under stress. This finding is consistent with the model of Adrian and Shin (2014) in which financial intermediaries adjust their risk exposures in reaction to changing economic conditions, in order to maintain a constant probability of default. Third, consistent with banks engaging in commonality in trading, we show that changes in risk exposures are positively correlated among banks. When contrasting periods of increasing volatility and periods of decreasing volatility, we find that the negative relationship between volatility and risk exposures and commonality in risk exposures is present in all market conditions.

Our paper makes several contributions to the literature on financial risk management. First, on the methodological side, we show how to extract an implied measure of changes in banks' risk exposures from publicly available data on VaR and volatility. By doing so, we complement Taylor (2005) who shows how to generate volatility forecasts from market risk disclosures. Second, we empirically document the presence of commonality in the risk exposures of large banks. Our decomposition of the changes in risk disclosure allows us to directly test for similarities in trading positions by looking at bank risk exposures and not at trading profit-and-loss data (Berkowitz, Christoffersen and Pelletier, 2011). In two distinct studies of large US banks, Berkowitz and O'Brien (2002) and Jorion (2006) both report a moderate correlation between US banks' trading profit-and-loss, which suggests that there is significant heterogeneity in banks' risk exposures. Differently, our study of the joint dynamics of banks' risk exposures indicates that banks rebalance their trading portfolios in a correlated way. Third, we contribute to the debate on the procyclicality of regulatory capital. We report a negative correlation between market volatility and risk exposures, which suggests that banks actively manage their risk exposures according to market conditions. This contrarian risk-taking behavior can be seen as an attempt to damper the procyclicality of bank regulatory capital. Fourth, as our methodology relies on a certain degree of commonality in volatility across the assets within a given asset class, we show that the factor structure recently documented by Herskovic et al. (2014) for the volatility of equity is persistent across asset classes.

Our study is also related to the theory on the propagation of financial shocks. In their generalequilibrium model, Pavlova and Rigobon (2008) show that portfolio constraints, such as VaR constraints, can increase the comovement of the stock prices. While in their framework, only one agent is constrained in his portfolio choice, we consider a situation in which many financial institutions may be forced to curb their positions due to the tightening of their constraints. Furthermore, as banks tend to rebalance their risk exposures at the same time and in the same direction after a shock, our study provides empirical evidence in support of the theoretical predictions of Danielsson, Shin, and Zigrand (2004), which state that VaR constraints can exacerbate shocks further.

The outline of the paper is as follows. In Section 2, we present a methodology allowing us to extract information about changes in banks' risk exposures from public data. Section 3 presents the empirical analysis using actual VaR data for a sample of large US and international banks. We show in Section 4 how to extend the methodology to other types of risk disclosures and to time-varying skewness and kurtosis. Section 5 summarizes and concludes our study.

2 FIRE Methodology

2.1 Theory

When the distribution of the (demeaned) returns belongs to the location-scale family, the conditional VaR of an asset can be expressed as:

$$VaR_t = -\ \sigma_t\ F^{-1}(\alpha)\ W_t \tag{1}$$

where σ_t is the conditional volatility of the asset return, $F^{-1}(\alpha)$ is the α-quantile of the standardized return distribution, and W is the dollar amount invested in the asset (Jorion, 2007). We see that there are two factors driving the VaR in this set-up, namely the volatility and the amount invested.[3] The change in amount invested can be due to the return of the asset or to inflow/outflow from the investor. The change in VaR is given by:

$$\Delta VaR_t = VaR_{t+1} - VaR_t \tag{2}$$

$$= - F^{-1}(\alpha)\Big(\sigma_{t+1}\, W_{t+1} - \sigma_t\, W_t\Big). \tag{3}$$

While this relation only holds if $F^{-1}(\alpha)$ remains constant over time, we relax this assumption in Section 4.2. Under this assumption, the percentage change in VaR is:

$$\frac{\Delta VaR_t}{VaR_t} = \frac{- F^{-1}(\alpha)\Big(\sigma_{t+1}\, W_{t+1} - \sigma_t\, W_t\Big)}{- \sigma_t\, F^{-1}(\alpha)\, W_t} \tag{4}$$

or equivalently

$$1 + \%\Delta VaR_t = \Big(1 + \%\Delta\sigma_t\Big)\Big(1 + \%\Delta W_t\Big). \tag{5}$$

As a result, the percentage change in the dollar amount invested in the asset is:

$$\%\Delta W_t = \frac{1 + \%\Delta VaR_t}{1 + \%\Delta\sigma_t} - 1. \tag{6}$$

This equation is extremely useful. It allows us to infer the change in amount invested (unknown) from the change in VaR and volatility (both being observed).[4]

Although our methodology is very general, we focus in this paper on the actual risk disclosures of financial institutions. A common practice at large banks is to disclose their VaR for each risk factor, such as equity, interest rate, FX, and commodity (Pérignon and Smith, 2010; Basel Committee on Banking Supervision, 2011). Specifically, a factor VaR indicates the maximum loss, at the $1 - \alpha$ confidence level over a given horizon, that can be due to a given source of

[3] The two-dimensional nature of VaR is made clear in Goldman Sachs' 2013 10-K report (page 103): "*even if our positions included in VaR were unchanged, our VaR would increase with increasing market volatility and vice versa*".

[4] With non-zero mean processes, the conditional mean of the return needs to be subtracted in Equation (1). However, given the short horizon considered, the variance term is much larger than the mean so that the mean can safely be ignored.

risk. For each bank i, we model the bank return on factor f, R_{ift}, as a function of the factor return, R_{ft}, and an idiosyncratic return, ε_{ift}:

$$R_{ift} = \beta_{ift}\ R_{ft} + \varepsilon_{ift}. \tag{7}$$

For instance, for equity, this means that the return on the bank's equity portfolio can be imperfectly correlated with the US equity market, as proxied by the S&P 500 stock index. The idea behind the one-factor structure is that we focus on a subportfolio that is predominantly affected by one major source of risk (e.g. equity portfolio, commodity portfolio). From Equation (7), we can express the variance of R_{ift}, σ^2_{ift}, as:

$$\sigma^2_{ift} = \beta^2_{ift}\ \sigma^2_{ft} + \sigma^2_{\varepsilon t} \tag{8}$$

where σ^2_{ft} is the variance of the factor return and $\sigma^2_{\varepsilon t}$ is the variance of the idiosyncratic return.[5] In that case, VaR is defined as:

$$\begin{aligned} VaR_{ift} &= -\ \sigma_{ift}\ F^{-1}_{if}(\alpha)\ W_{ift} && (9) \\ &= -\ \sqrt{\beta^2_{ift}\ \sigma^2_{ft} + \sigma^2_{\varepsilon t}}\ F^{-1}_{if}(\alpha)\ W_{ift} && (10) \end{aligned}$$

and Equation (1) becomes:

$$VaR_{ift} = -\ \sigma_{ft}\ F^{-1}_{if}(\alpha)\ E_{ift} \tag{11}$$

where $F^{-1}_{if}(\alpha)$ is the α-quantile of the standardized factor return and E_{ift} is the risk exposure of firm i with respect to factor f at time t, which is defined by:

$$\begin{aligned} E_{ift} &= W_{ift}\sqrt{\beta^2_{ift} + \frac{\sigma^2_{\varepsilon t}}{\sigma^2_{ft}}} && (12) \\ &\simeq W_{ift}\ \beta_{ift} \quad \text{when } \sigma_{\varepsilon t} \ll \sigma_{ft}. && (13) \end{aligned}$$

[5] Consistent with Equation (8), Herskovic et al. (2014) show that there exists a strong factor structure for the volatility of equities. We show in Section 2.5 that other asset classes also exhibit strong volatility factor structures.

What this expression tells us is that there are two main ways for a bank to modify its risk exposure: first, the bank can change the dollar amount invested in the portfolio and second, it can modify the sensitivity of its portfolio with respect to a risk factor.[6] The change in VaR is given by:

$$\Delta VaR_{ift} = -\ F_{if}^{-1}(\alpha)\Big(\sigma_{ft+1}\ E_{ift+1} - \sigma_{ft}\ E_{ift}\Big) \tag{14}$$

and the percentage change in VaR is:

$$\begin{aligned} \frac{\Delta VaR_{ift}}{VaR_{ift}} &= \frac{-\ F_{if}^{-1}(\alpha)\Big(\sigma_{ft+1}\ E_{ift+1} - \sigma_{ft}\ E_{ift}\Big)}{-\ \sigma_{ft}\ F_{if}^{-1}(\alpha)\ E_{ift}} && (15) \\ 1 + \%\Delta VaR_{ift} &= \Big(1 + \%\Delta\sigma_{ft}\Big)\Big(1 + \%\Delta E_{ift}\Big). && (16) \end{aligned}$$

The percentage change in risk exposure between dates t and $t+1$ is given by:

$$\%\Delta E_{ift} = \frac{1 + \%\Delta VaR_{ift}}{1 + \%\Delta\sigma_{ft}} - 1. \tag{17}$$

Equation (17) is the key result of the FIRE methodology. It gives an expression for the changes in risk exposure as a function of the changes in VaR and in the volatility of the risk factor.

It is important to notice that the FIRE methodology works with both long and short positions. For a short position, the VaR is defined by:

$$VaR_{ift} = -\ \sigma_{ift}\ F_{if}^{-1}(1-\alpha)\ E_{ift} \tag{18}$$

with $E_{ift} < 0$ (Giot and Laurent, 2003). In that case, the percentage change is also given by Equation (15) and the percentage change in risk exposure by Equation (17).[7]

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[6] If no single exposure in the portfolio accounts for more than an arbitrarily small share of the portfolio, then the variance of the portfolio return obtained when the portfolio size tends to infinity is fully determined by the variance of the common factor and $\sigma_{\varepsilon t} \ll \sigma_{ft}$ (see Gordy, 2003).

[7] If we further assume that the marginal distribution F is symmetric, then the VaR becomes $VaR_{ift} = -\sigma_{ift}\ F_f^{-1}(\alpha)\ |E_{ift}|$ for both long and short positions. Under the symmetry assumption, the FIRE methodology is robust to a change in position from a long position to a short position, and vice versa. In the symmetric case, the percentage change in risk exposure is still given by Equation (17).

2.2 The Main Assumption under the FIRE Methodology

The main assumption in the FIRE methodology is that the quantile $F^{-1}(\alpha)$ is constant through time. In the one-asset case (Equations (1)-(4)), the quantile remains constant as long as the distribution of the asset return does not change from one date to the next. In the case of a portfolio (Equations (9)-(15)), there are two sources of time variation in the quantile of the portfolio return distribution: changes in the distribution of the assets and changes in the portfolio weights. However, even when the weights are time-varying, the quantile remains constant if we consider conditional distributions for the asset returns that are closed in aggregation (e.g. normal distribution). Otherwise, the generalized FIRE presented in Section 4.2 has to be used in order to take into account the time variation in the quantile.

Conversely, when the portfolio contains a *large* number of assets, as it is most likely the case for the trading portfolios of the large banks studied in this paper, this distribution assumption can be relaxed. On a given date, if the number of assets tends to infinity and the bank's portfolio is sufficiently diversified, the conditional distribution of the portfolio return tends to a normal distribution, as the Central Limit Theorem applies. As a consequence, the quantile of the standardized portfolio return converges towards $\Phi^{-1}(\alpha)$ and there is no need to assume that the distributions are closed in aggregation. This limiting argument applies even if the individual returns are heterogeneously conditionally distributed (Liapounov Central Limit Theorem, see Greene, 2012, page 1082) and when the returns are weakly dependent in the cross-sectional dimension (see Bajgrowicz and Scaillet, 2012).

2.3 Case Study on Goldman Sachs

In order the check whether the changes in risk exposures produced by the FIRE methodology make economic sense, it would be ideal to compare the *estimated* risk exposure changes to the *actual* risk exposure changes. As the latter are typically unknown to the public, such comparison is hard to make in practice. However, we found one firm for which the comparison is possible. Indeed, Goldman Sachs makes some statements in its quarterly public filings about the recent changes in its trading portfolio. To our knowledge, Goldman Sachs is the only financial institution to make such public announcements in a systematic way over an extended period of time.

To be able to extract the implied risk exposures, we collect quarterly equity VaR figures from all Goldman Sachs 10-Q forms between 2003Q1 and 2013Q3. These figures are one-day 95% VaRs averaged over a given quarter. Furthermore, we control for contemporaneous changes in volatility in the stock market using the VIX index. Figure 1 displays the quarterly values of the equity VaR along with the VIX index (both are average measures over the quarter). Eyeballing the figure shows little covariation between the VaR and the market volatility. In fact, if anything, the correlation is negative.[8] For instance, the sharp increase in volatility between 2007 and 2008 corresponds to a period of massive reduction in equity VaR for the firm. The negative relationship between equity VaR and VIX may seem surprising at first sight, and especially if we refer to the abundant literature on tail risk in which the positive relationship between tail risk and volatility is crucial (see for instance the excellent survey by Christoffersen, 2009). The fundamental positive relationship between VaR and volatility is

[8] We obtain similar pattern when we replace the VIX by the standard-deviation of daily returns on the S&P500 stock index using a three-month estimation window.

of course true if the risk exposure remains constant through time. However, in practice, this condition is violated as trading positions can significantly vary from one quarter to the next.

< Insert Figure 1 and Table 2 >

For each quarter Q in year Y, we extract the change in equity risk exposure between quarter Q in year Y and quarter Q in year Y-1 using the FIRE methodology. We display the changes in equity VaR, volatility, and risk exposure in Table 2. We notice that the VaR increased steadily between 2003 and 2007 whereas the volatility decreased over the same period. This preliminary piece of evidence confirms that VaR is not only driven by the volatility and that changes in risk exposure are likely to play an important role in the dynamics of the risk disclosure. The relationship between the VaR and the market volatility remains negative over the entire sample period. Differently, the changes in VaR and in risk exposures are positively correlated.

As a cross-validation exercise, we contrast the risk exposure estimates with statements made by the firm about its current equity risk exposure. In each quarterly report, Goldman Sachs complements the VaR figures with information about any substantive changes in its investment strategy over the past year. For instance, in its 10-Q form dated May 2008, Goldman Sachs mentions that "*Our average daily VaR increased to $184 million for the second quarter of 2008 from $133 million for the second quarter of 2007. The increase was primarily due to higher levels of volatility [...]. These increases were partially offset by a decrease in exposures to equity prices*". Over this particular period (2008Q2 vs. 2007Q2), the FIRE methodology successfully indicates the direction of the change in risk exposures. It generates a 51% decrease in implied risk exposure for equity while, at the same time, the VIX index increased by 61%.

We conduct a similar analysis for all 30 quarterly reports between 2004Q1 and 2013Q3. For each quarter, we compare the change in equity risk exposure provided by the FIRE methodology with the information disclosed by the firm in its 10-Q report. As shown in Table 2 and Figure 2, we have not found a single case in which the FIRE estimate and the 10-Q form contradict each other. Note that this result is not due to any major trend in risk exposures as reductions in risk exposures are almost as frequent as increases in risk disclosure in our sample (nine decreases and eleven increases). Furthermore, there are another ten quarters for which Goldman Sachs made no particular comments. Interestingly, we notice that these quarters correspond to periods during which the equity risk exposure revealed by the FIRE was more stable. We find that during high VaR change quarters ($|\Delta VaR/VaR| \geqslant 30\%$), the firm makes comments in 94.1% of the cases (16 out of 17 quarters), whereas during low VaR change quarters ($|\Delta VaR/VaR| < 30\%$), the firm makes comments in only 30.8% of the cases (4 out of 13 quarters).

We consider a series of robustness checks. First, we replace average VaR and VIX values by their end-of-quarter values. We, again, systematically compare the estimated change in risk exposures given by the FIRE methodology to actual statements made by the firm for the 30 different quarters. Second, we conduct a similar analysis using annual 10-K forms between 2004 and 2013, which leads to another 20 comparisons. In annual reports, the company compares its average (respectively year-end) equity-risk exposures in year Y to its average (respectively year-end) equity-risk exposures in year Y-1. For these 50 comparisons, there are specific comments from the firm in 27 cases. In two cases only the sign of the change in implied risk exposure does not match the company's report. However, in both cases, the implied changes in risk exposures is small (-2% and 6%), which makes misclassification more likely.

Overall, the results in this case study are encouraging. Despite the assumptions we made about the distribution and the factor structure of the return, the FIRE methodology seems to produce some risk estimates that fit well with reality. In Section 3, we expand the analysis to more banks and factors and investigate the comovements in risk exposures across banks.

2.4 Monte Carlo Simulations

In practice, both the VaR and the volatility estimates can be affected by estimation risk or model risk. For instance, banks may not correctly and promptly incorporate dynamic volatility in their VaR models. This is for instance the case when the VaR is computed by historical simulation. In this section, we study by simulation the potential biases on the FIRE that come from estimation and model risks.

To better understand the problem, we need to distinguish three elements: (1) the true data generating process (DGP) of the return, (2) the internal model used by the bank to compute its VaR, and (3) the volatility model used by the econometrician to implement the FIRE method. For simplicity, we call the latter model the FIRE model.

In our context, there are two sources of model risk. First the bank VaR model may not match with the DGP (Escanciano and Olmo, 2011). For instance, the bank computes historical simulation VaRs whereas the DGP is a GARCH(1,1). Second, the FIRE model may not match with the bank VaR model. For instance, the econometrician uses a GARCH(1,1) model whereas the bank uses historical simulation. We will see below that only the latter type of model risk can be problematic to extract risk exposures.

Moreover, estimation risk is also at play as soon as the parameters of the bank VaR model and/or of the FIRE model have to be estimated (Gourieroux and Zakoian, 2013). When the parameters are estimated with errors, the resulting implied exposure may also be biased. It is well known that this bias tends to disappear as the sample size increases.

The basic idea of these simulations is to assume a particular process for the changes in the bank's risk exposure and to check whether the FIRE methodology correctly estimates them. For simplicity, we consider only one asset and some discrete exposures to ease the comparison between the true and estimated exposures. On each date, the bank's exposure in the asset is assumed to change by $\Delta W_t\%$, where $\Delta W_t\%$ is drawn from a multinomial distribution on {-20%, -15%, -10%, -5%, -2%, 2%, 5%, 10%, 15%, 20%} with equal probabilities.

In all experiments, the DGP of the asset return R_t is a GARCH(1,1) process.[9] Moreover, given its exposure and a simulated sample of the returns, denoted $\{R_t^s\}_{t=1}^T$, the bank computes its VaR using its internal risk model. We consider three types of internal models: a parametric model with estimated parameters (GARCH), a parametric model with fixed parameters (RiskMetrics) and a non-parametric method (historical simulation). Finally, bank VaRs are used to estimate the implied exposure of the bank with the FIRE methodology. In our simulations, we consider three types of FIRE volatility models: GARCH, RiskMetrics, and historical volatility based on a rolling window of 250 days.

We present our four experiments in Panel A of Table 3. In the first experiment, we consider the first type of model risk in which both the bank VaR model and the FIRE model are assumed to be RiskMetrics whereas the DGP is a GARCH(1,1). Note that there is no

[9] The parameters are the following: constant = $8.5965e^{-7}$, ARCH parameter = 0.0692, and GARCH parameter = 0.9242.

estimation risk in this case. In the second experiment, the bank VaR model is RiskMetrics and the FIRE model is a GARCH. Since the GARCH model nests RiskMetrics, there is no model risk in this case. However, since the GARCH parameters have to be estimated, estimation risk is present. In the third experiment, there is model risk (second type) but no estimation risk. The bank VaRs are produced by historical simulation and the FIRE is based on a historical volatility obtained with the same rolling estimation window. Finally in the fourth experiment, the bank uses historical simulation to produce its VaR whereas the FIRE is based on a GARCH model, inducing both model risk and estimation risk.

< Insert Table 3 >

In order to quantify the relative importance of model and estimation risks, we need to compare the true and implied risk exposures obtained for each simulation. This comparison is based on three statistical criteria: the percentage of matching signs, the Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE). We also report the average R^2 statistics obtained by regressing the true position change on a constant and the exposure extracted with the FIRE methodology. The sample size T ranges from 250 to 2,000 observations and we run 100,000 simulations for each experiment.

The results are reported in Panels B-E of Table 3. Overall, we observe that the percentage of positive matching signs between the true and implied changes in exposure is always greater than 92% (91% for the percentage of negative matching signs). This result indicates that the FIRE methodology accurately predicts the direction of the change in the true risk exposure. Moreover, the bias in the exposures is relatively small whatever the experiment and the sample size considered since the R^2 is always larger than 89%.

Several other conclusions can be drawn from this series of experiments. First, risk model does not affect the performance of the FIRE except if it stems from a mismatch between the bank VaR model and the FIRE model (see experiments 1 and 2). Second, according to all evaluation criteria and sample sizes, the bias is the largest in the fourth experiment. For instance, for a sample size of 250 observations, the MAE is about 0.5% in experiments 2 and 3 whereas it is equal to 3% in the fourth experiment. This result clearly indicates that estimation risk as modeled in experiment 2, or moderate model risk as modeled in experiment 3, have limited impact on the FIRE methodology. In particular, the influence of estimation risk is very limited even in small samples ($T = 250$). Third, the magnitude of the bias decreases with sample size when there is estimation risk. For instance in the second experiment, the MAE drops from 0.65% to 0.48% when the sample size goes from 250 to 2,000 observations. When only model risk is present, the MAE does not change with sample size. In experiment 3, it is constant and equal to 0.58%.

2.5 Commonality in Volatility Within an Asset Class

The FIRE methodology relies on a certain degree of commonality in volatility across the assets that belong to the same asset class, as shown in Equation (8). While Herskovic et al. (2014) have recently documented that equity volatility exhibit a strong factor structure, we test in Table 4 whether this holds true for other asset classes, such as fixed income, foreign exchange, and commodity. We follow Herskovic et al. (2014) and regress, for each asset, the asset-level volatility, σ_{ift}, on the equally-weighted average of volatility within the asset class f, $\overline{\sigma_{ft}}$:[10]

[10] While Herskovic et al. (2014) also document commonality in idiosyncratic volatility, we only test for commonality in total volatility since the FIRE methodology is based on total volatility. In each regression, we require a minimum of 10 observations.

$$\sigma_{ift} = \text{intercept}_i + \text{loading}_i \; \overline{\sigma_{ft}} + e_{ift}. \tag{19}$$

The volatility measures are the historical standard-deviations of the daily returns, which are available for the period January 1, 1999 to June 20, 2014 (respectively, end of 2013 for equities). For equity, we extract from CRSP the daily returns of the 500 constituents of the S&P 500 stock index at the end of 2013. For fixed income, we extract from the FRED database the daily yields of all (148) securities within four categories: commercial papers (30), corporate bonds (98), Treasury bills (4), and Treasury constant maturity (16). For FX, we select the ten largest currencies based on the percentage shares of average daily turnover in April 2013 (BIS, 2013).[11] Then, we extract from Bloomberg the daily exchange rates for the 45 pairs of currencies and compute their daily returns. For commodities, we consider the constituents of the Dow Jones-UBS Commodity Index. To avoid issues due to expiration dates, we extract from Bloomberg the price of the Generic 1st month Futures for 20 components of the commodity index, as well as the S&P GSCI Kansas Wheat Index.[12]

Table 4 reports the cross-sectional averages of the intercept and loading coefficient estimates and of the R^2 for each asset class. In this table, we consider three frequencies: yearly in Panel A (like in Herskovic et al., 2014), quarterly in Panel B (like in the rest of this study), and monthly in Panel C. The main conclusion from all three panels is that the high degree of commonality in volatility discovered by Herskovic et al. (2014) for equities, is persistent across all main asset classes. The cross-sectional average R^2 is particularly high for equity

[11] The list of currencies, sorted in decreasing order of importance, includes the US Dollar, Euro, Japanese Yen, British Pound, Australian Dollar, Swiss Franc, Canadian Dollar, Mexican Peso, Chinese Renminbi, and New Zealand Dollar.

[12] The 20 Generic 1st month Futures are Natural Gas, WTI Crude Oil, Brent Crude Oil, Heating Oil, Live Cattle, Lean Hogs, Wheat, Corn, Soybeans, Soybean Oil, Soybean Meal, Aluminum, Copper, Zinc, Nickel, Gold, Silver, Sugar, Cotton, and Coffee.

(56.3%-66.8%), interest rate (45.1%-50.9%), foreign exchange (52.2%-59.2%), and slightly lower for commodities (29.5%-34.1%). Note that for some asset classes, the average intercept and slope coefficients differ from zero and one, respectively, because of the unbalanced panel structure of the data. We also notice that for equity, the R^2 reported in Table 4 with a yearly frequency tend to be higher than those in Herskovic et al. (2014), which are around 0.35. This difference is likely due to the much longer sample period (1926-2010) and much broader cross-section of assets (20,000 stocks) considered in their original study. We complement the univariate analysis by displaying the R^2 of a pooled regression obtained from a panel regression model with securities' fixed-effects (within estimator). The results indicate that our findings are robust in a panel model that imposes common loadings for all the assets. The degree of commonality in volatility remains particularly strong within equities and fixed income securities.

< Insert Table 4 >

3 Changes in Risk Exposures at Large Banks

3.1 First Input: VaR

In this section, we study the actual changes in risk exposures at large banks before, during, and after the 2008 crisis. These risk exposure changes are extracted from the VaR of ten large US and international banks between 2007Q3 and 2013Q3 (see Appendix for a list of the sample banks). VaR figures are publically disclosed in the quarterly and annual reports of the firms. These reports have been retrieved from the EDGAR database for US banks and from the firms' websites for international banks. The VaR figures typically have a one-day horizon and a 99% confidence level and are available on four different risk factors: equity, interest rate, FX, and commodity. In our tests, we use end-of-quarter VaRs for all banks, except for Bank of America and BNP Paribas for which we use average VaRs over the quarter.[13]

We first show in Figure 3 and Table 5 that the factor VaRs only exhibit some weak positive covariation across banks. Figure 3 displays the Value-at-Risk of four sample banks (Citigroup, Credit Agricole, Credit Suisse, and Deutsche Bank). We notice in this graph that the evolution of the VaR is quite erratic, with large changes from one quarter to the next. It is indeed not uncommon to see a VaR changing by a factor of 3 or 5 within a given year. For some risk types, there is a common trend over the sample period. For instance, the interest-rate VaR of all banks increased over 2007-08 and decreased afterwards. Similarly, there is a clear negative trend for equity risk starting at the end of 2008. Differently, there is much less comovement in the FX and commodity VaRs for these banks. We extend the analysis to all sample banks in Table 5 and report the average correlation between the quarterly VaR of a bank, VaR_{ift}, and the quarterly VaR of all other sample banks for each risk factor, VaR_{jft}, $j \neq i$ (upper panel). We report a positive average correlation for all four risk factors, which reflects the fact that VaR numbers are affected by some common volatility shocks. However, the magnitude of these correlations is not very high: in the 40%-45% range for equity and interest rate and less than 20% fo FX and commodity. Furthermore, we measure in the lower panel of Table 5 the frequency with which the VaRs of banks i and j move in the same direction. The percentage of matching signs between ΔVaR_{ift} and ΔVaR_{jft} is rather low, between 44% and 57%.

< Insert Figure 3 and Table 5 >

[13] Our initial sample was the largest 25 banks in the world according to their total assets as of June 2012. We then selected all banks disclosing end-of-quarter or average VaRs for the four main risk factors (equity, interest rate, foreign exchange, and commodity). Then, we selected the longest possible sample period allowing us to get a balanced panel. See the Appendix for more details about the VaR figures.

3.2 Second Input: Volatility

In order to control for concurrent changes in volatility, we use some factor volatility indices. These indices are extracted from options written on the different underlying factors and with maturities between one and three months. Specifically, we use the CBOE VIX index to proxy the volatility of the equity market. The volatility on the fixed income market is measured by the Merrill Lynch Move index, which tracks the implied volatility of Treasury bond prices. The volatility on the FX market is measured by the CVIX, a measure of implied volatility of major currency exchange rates. Finally, the volatility on the commodity market is measured by the OVX, a measure of implied volatility in West Texas Intermediate crude oil prices.[14] We display the evolution of the volatility of each risk factor in Figure 4. As expected, there is strong commonality in the volatility of these risk factors, with spikes after the Lehman collapse in October 2008 and the European sovereign-debt crisis during the summer 2011.

< **Insert Figure 4** >

We show in Table 6 that the VaR and the factor volatility tend to be positively correlated for all risk factors.[15] The average correlation is lowest for commodity (16%) and highest for interest rate (53%). We also notice that this correlation is not positive for all banks. In fact, there are only five banks in our sample for which the correlation is positive for all four factors. Furthermore, when we compute the percentage of matching signs between the changes in VaR and in volatility, we find a frequency in the 40%-55% range. This finding suggests that in many occasions, the evolutions of the bank risk disclosures and market volatility diverge.

[14] We use the same volatility indices as in the Risk (2010) annual VaR survey. We obtain daily data on the factor volatility indices from Bloomberg and Datastream.

[15] For banks that disclose end-of-quarter VaRs, the correlation is computed using end-of-quarter volatility. Similarly, for banks that disclose average VaRs, the correlation is computed using average volatility.

Another implication of our preliminary set of results is that market volatility does not seem to be a dominant driving force for factor VaR.

< Insert Table 6 >

3.3 Implied Risk Exposures

To formally gauge the impact of volatility and risk exposure changes on VaR, we implement the FIRE methodology that was presented in Section 2. For each bank/quarter, we plug the percentage change in VaR and the percentage change in volatility into Equation (17) to get the implied risk exposure variation for each risk factor. To have a first look at the results, we superimpose the evolution of the VaR, volatility, and implied risk exposure for equity in Figure 5. The message we obtain is unambiguous: the change in risk exposures is the main driving force for equity VaR.

Another important finding is that changes in risk exposure and volatility tend to move in opposite directions. We analyze the relationship between risk exposure and volatility for all factors and all banks in Table 7. In the upper panel of the table, we show that the percentage changes in risk exposure and volatility are negative for virtually all firms and all factors. On average, this correlation is -53% for equity, -56% for interest rate, -25% for FX, and -56% for commodity. Moreover, as shown in the lower panel of Table 7, rarely do the changes in risk exposure and volatility move in the same direction.

Our conclusion on the negative relationship between risk exposures and market volatility is consistent with the model and empirical findings of Adrian and Shin (2014). They claim that financial firms cut back their asset exposure when the environment becomes more risky in order to maintain a constant probability of default. They show that large US banks reacted to the volatility spike in 2008 by sharply reducing their leverage. At the same time, the VaR to equity ratio barely changed.

< **Insert Figure 5 and Table 7** >

We then move to the cross-sectional analysis of banks' risk exposures. To test whether risk exposures are correlated across banks, we report in the upper panel of Table 8 the average correlation between the percentage change in risk exposure of a bank, $\%\Delta E_{ift}$, and the percentage change in risk exposure of all other sample banks, $\%\Delta E_{jft}$, $j \neq i$. The lower panel of this table displays the frequency with which changes in risk exposure of banks i and j move in the same direction. The main takeaway from this table is that there is some strong commonality in bank risk exposures. Indeed, 39 out of the 40 average correlation coefficients among the changes in risk exposures are positive. Moreover, risk adjustments at two random sample banks go in the same direction between 58% and 66% of the time, which is between 5 and 22 percentage points higher than the values for the VaR in Table 5.

< **Insert Table 8**>

We also model changes in risk exposures using a multivariate panel regression. Our baseline specification is:

$$\%\Delta E_{ift} = \delta_i + \delta_1 \, \overline{\%\Delta E_{jft}} + \delta_2 \, \%\Delta\sigma_{ft} + \delta_3 \, R_{ft} + \delta_4 \, CDS_{it} + \delta_5 \, RoE_{it} + e_{ift} \qquad (20)$$

where δ_i is a bank-specific intercept, $\overline{\%\Delta E_{jft}} = \sum_{i \neq j} \%\Delta E_{jft}/(N-1)$ denotes the average percentage change in banks' risk exposures, $\%\Delta\sigma_{ft}$ is the percentage change in factor volatility,

R_{ft} denotes the quarterly return of the risk factor, CDS_{it} is the senior 5-year CDS of the bank, and RoE_{it} is the bank quarterly return on equity.[16] The δ_1 parameter aims to capture any commonality in risk exposures among banks whereas the δ_2 parameter measures the relationship between risk exposure and market volatility.

In our tests, we use the following indices for the four risk factors: S&P500 Index (equity), 3-Year Treasury Constant Maturity Rate (interest rate), Trade Weighted U.S. Dollar Index (FX), and Dow Jones-UBS Commodity Index (commodity). The data have been retrieved from Datastream and the Federal Reserve Economic Database (FRED) and cover the period 2007Q3-2013Q3.

We present the estimation results in Table 9 for each risk factor (columns 1-8) and then for all risk factors stacked together (columns 9-10). We find evidence of strong commonality in risk exposures as the OLS estimated coefficients associated with other banks' risk exposures are positive and significant ($\hat{\delta}_1 > 0$). This finding holds true for all factors but the effect is particularly strong for equity and interest rate. This result is suggestive of commonality in risk exposures due to similar investment or hedging policies across banks. We also report a negative and significant relationship between risk exposure and factor volatility ($\hat{\delta}_2 < 0$), which is consistent with the univariate results in Table 7. We however find no evidence that banks with particularly poor performance or higher probability of default tend to take on more risk (risk shifting). We also notice that the inclusion of the control variables (R_{ft}, CDS_{it}, RoE_{it}) does not alter our conclusions on commonality in risk exposures and on the relationship between risk exposure and market volatility, with the exception of FX.

[16] The CDS data were retrieved from Datastream and the RoE from the banks' quarterly and annual reports.

< Insert Table 9 >

3.4 Robustness Checks

We consider a series of robustness checks. First, we use alternative proxies for the average change in banks' risk exposures. We replace the equally-weighted commonality proxy by a value-weighted commonality proxy (Table 10, Panel A) and by the first principal component of the covariance matrix of the percentage changes in risk exposures (Table 10, Panel B). Overall we find that our result on commonality in risk exposures remains strong and significant with all commonality proxies. Second, we change the volatility proxy for the risk factors. Instead of using implied volatility indices, we compute historical volatility measures within a given quarter. Specifically, we compute the 3-month historical standard deviation of the return of the risk factor (Table 10, Panel C). Using these new proxies for volatility changes, we recompute the implied change in risk exposures using the FIRE method and re-run our regression. Overall, we see that our main findings are robust to this change of volatility proxy.

< Insert Table 10 >

Several reasons can explain the commonality in risk exposures documented in Tables 9 and 10. First, banks can rebalance their trading portfolios in a correlated way because of common information. Second, they may have to curb risk at the same time because they face similar regulatory constraints. For instance, when several banks operate at their VaR limit, even a small increase in volatility would force them to unwind their positions in a correlated way. Third, the exposure of two banks with respect to a given factor can also increase because the return of this factor was positive. In order to control for the latter effect, we estimate the following panel regression:

$$\%\Delta E_{ift} - R_{ft} = \theta_i + \theta_1 \overline{\%\Delta E_{jft} - R_{ft}} + \theta_2 \ \%\Delta\sigma_{ft} + e_{ift} \tag{21}$$

where $\overline{\%\Delta E_{jft} - R_{ft}}$ is $\sum_{i \neq j}(\%\Delta E_{jft} - R_{ft})/(N-1)$. In this specification, we systematically remove the return on the factor from the change in risk exposure. Results in Panel D of Table 10 clearly indicate that commonality in risk exposures is not mainly due to factor returns. Indeed, the coefficient associated with other banks' changes in risk exposures (θ_1) remains positive and significant for all factors, at least at the 10% confidence level. We also notice that the strong negative relationship between volatility and risk exposure is preserved (θ_2).

Finally, in order to test whether our conclusions remain valid in different market conditions, we split the sample into two subperiods. The first one covers 2007Q3-2008Q4 and corresponds to a period of sharp increase in market volatility (see Figure 4). The second subperiod, 2009Q1-2010Q1, corresponds to a period of massive reduction in market volatility. We show in Table 11 that the quarterly average change in factor volatility ranges between 22% and 27% in the first period and between -11% and -18% in the second period. Overall, we find that our conclusions about the dynamics of the risk exposures are persistent through the different phases of the volatility cycle. In particular, we find that the negative relationship between changes in volatility and risk exposure is a robust feature of the data. Furthermore, we report evidence of commonality in risk exposures across banks in both volatility regimes.

< Insert Table 11 >

4 Extensions

4.1 Other Types of Risk Disclosures

So far in this study, we have only focused on one type of bank risk disclosure, namely the VaR. We now show how to infer information about risk exposures from other types of banks' risk disclosures. Under Basel III, all financial institutions with material trading activities must compute both their VaR using recent data and their *stressed* VaR (sVaR) using data from a particularly volatile period (Basel Committee on Banking Supervision, 2011; Rossignolo, Fethi and Shaban, 2013). This measure is intended to replicate a VaR calculation that would be generated on the bank's current portfolio if the relevant market factors were experiencing a period of stress. As an example, for many portfolios, a 12-month period relating to significant losses in 2007/2008 would adequately reflect a period of such stress.

The stressed VaR is an important innovation in financial risk management. The Ernst & Young (2012) survey of financial services risk management reveals that stress testing and stressed VaR have been the top two areas of improvement in 2012: 55% of the respondents identify stressed VaR as the top area of improvement in transparency. Moreover, under Basel III, stressed VaR is included in the computation of the capital requirements for market risk, c_t:

$$c_t = \max\{VaR_t; m \cdot VaR_{avg}\} + \max\{sVaR_t; m_s \cdot sVaR_{avg}\} \tag{22}$$

where m and m_s are two positive multiplicative factors set by the regulators and subject to an absolute minimum of 3, and the *avg* subscript stands for an average computed over sixty business days.

We show in this section that it is possible to use the FIRE methodology with stressed, instead of standard, VaR figures. In fact, it turns out that it is much easier to learn about changes in risk exposures from stressed VaRs than it is from standard VaRs. The reason being that changes in stressed VaR are only due to changes in risk exposures, and not to changes in volatility (recall that, with stressed VaR, volatility is always measured during the same high-volatility period). We make this point formally by defining the stressed VaR as:

$$sVaR_t = -\Sigma\ F^{-1}(\alpha)\ E_t \tag{23}$$

where Σ denotes the conditional variance of the return measured over a particularly volatile period. We note that the variance parameter is not changing from one day to the next as it refers to a given high-volatility episode in the past. As a result, the change in stressed VaR is given by:

$$\begin{aligned} \Delta sVaR_t &= sVaR_{t+1} - sVaR_t && (24) \\ &= -\Sigma\ F^{-1}(\alpha)\ \Big(E_{t+1} - E_t\Big). && (25) \end{aligned}$$

The percentage change in VaR is:

$$\begin{aligned} \frac{\Delta sVaR_t}{sVaR_t} &= \frac{-\Sigma\ F^{-1}(\alpha)\ \Big(E_{t+1} - E_t\Big)}{-\Sigma\ F^{-1}(\alpha)\ E_t} && (26) \\ &= \frac{E_{t+1} - E_t}{E_t}. && (27) \end{aligned}$$

Then, we conclude that:

$$\%\Delta sVaR_t = \%\Delta E_t. \tag{28}$$

This equation shows that changes in stressed VaR only reflect changes in risk exposures. Unlike with standard VaR, changes in stressed VaR are completely immunized from volatility shocks, which greatly simplifies the analysis.

4.2 Generalized FIRE with Time-Varying Skewness and Kurtosis

It was shown in Section 2 that the α-quantile, $F^{-1}(\alpha)$, of the standardized return distribution must be constant for the FIRE to work. Obviously, if the skewness and/or the kurtosis of the conditional distribution of the returns are/is dynamic, the α-quantile may not be constant anymore and the implied exposure given by FIRE can be biased. To illustrate this, we consider a simple model in which the return is given by $R_t = \sigma_t \ \varepsilon_t$ where ε_t is *i.i.d.* with $\mathbb{E}(\varepsilon_t) = 0$ and $\mathbb{V}(\varepsilon_t) = 1$. Denote by $F_t(.)$ the cumulative density function, s_t the skewness and k_t the kurtosis of the distribution of ε_t. Using the Cornish-Fisher expansion, we know that for any $\alpha \in [0,1]$:

$$F_t^{-1}(\alpha) = z_\alpha + \frac{s_t}{6}\left(z_\alpha^2 - 1\right) + \left(\frac{k_t - 3}{24}\right)\left(z_\alpha^3 - 3z_\alpha\right) - \frac{s_t^2}{36}\left(2z_\alpha^3 - 5z_\alpha\right) \tag{29}$$

where $z_\alpha = \Phi^{-1}(\alpha)$ denotes the α^{th} quantile of the standard normal distribution. Then, if s_t or k_t is dynamic, $F_t^{-1}(\alpha)$ is not constant over time. As a consequence, a generalized version of the implied exposure becomes:

$$\%\Delta W_t = \frac{1 + \%\Delta VaR_t}{(1 + \%\Delta\sigma_t)\left(1 + \%\Delta F_t^{-1}(\alpha)\right)} - 1 \tag{30}$$

with $1 + \%\Delta F_t^{-1}(\alpha) = F_{t+1}^{-1}(\alpha) / F_t^{-1}(\alpha)$. In this case, we need to make an assumption on the dynamics of s_t and k_t. For instance, we can use the generalized skewed Student's t distribution of Hansen (1994) with ARCH-type models for the skewness and kurtosis, or the extension of Harvey and Siddique (1999, 2000).

At this point, a natural question arises. What is the cost of neglecting the dynamics of the skewness and kurtosis when extracting risk exposures? One way to answer this question is to compare the exposures given by the FIRE and a generalized version of the FIRE allowing for time-varying skewness and kurtosis. The difference in exposure depends on the value of $1+\%\Delta F_t^{-1}(\alpha)$. From Equation (29), we get:

$$\begin{aligned} 1+\%\Delta F_t^{-1}(\alpha) &= 1+\left(\frac{z_\alpha^2-1}{6}\right)\%\Delta s_t+\left(\frac{z_\alpha^3-3z_\alpha}{24}\right)\%\Delta k_t \\ &\quad -\frac{\left(2z_\alpha^3-5z_\alpha\right)}{18}\, s_t\, \%\Delta s_t. \end{aligned} \tag{31}$$

For $\alpha=0.01$, $s_t=-0.2$, and a range of $[-10\%, 10\%]$ for both $\%\Delta s_t$ and $\%\Delta k_t$, the value of $1+\%\Delta F_t^{-1}(\alpha)$ remains between 0.9181 and 1.0819. This means that the size of the bias of the exposure induced by neglecting the dynamics of the skewness and/or kurtosis ranges from -8.92% to 7.57%. Moreover, we notice in Equation (31) that $\%\Delta F_t^{-1}(\alpha)$ is more sensitive with respect to the skewness than to the kurtosis. Indeed, the partial derivative with respect to the change in skewness is $\left(z_\alpha^2-1\right)/6-\left(2z_\alpha^3-5z_\alpha\right)s_t/18=0.5848$ and the partial derivative with respect to the change in kurtosis is $\left(z_\alpha^3-3z_\alpha\right)/24=-0.2338$.

5 Conclusion

Because of the G20 Data Gap Initiative, more data will have to be disclosed by financial institutions to allow policy makers and supervisors to better assess the evolution of the financial system, as well as the intervention required (Cerutti, Claessens and McGuire, 2014). However, opportunities to observe actual positions or risk exposures of banks remain extremely rare in practice (e.g. European Banking Authority's 2011 stress tests). In this paper, we present FIRE, a new technique to infer banks' risk exposures from current public disclosures; very much in the spirit of implied volatility extracted from option prices.

The performance of the FIRE turns out to be quite good in practice, despite the assumptions made to derive our key result. In the case study on Goldman Sachs, we show that the implied risk exposures are systematically in line with the statements made by the firm about its risk taking in public filings. We believe that this is reassuring evidence that our method provides meaningful estimates. In addition, we assess the performance of the FIRE by simulation by considering several situations in which model risk and estimation risk could arise. Overall, we show that, in most situations, the bias induced by model and estimation risks remains moderate.

Using a sample of large US and international banks, we find that the main driving force of bank risk disclosures is the shifts in risk exposures and not market volatility. Furthermore, we show that changes in risk exposures are negatively correlated with volatility changes, which suggests that banks aim to reduce the variability of their VaR and regulatory capital. Most importantly, we provide empirical evidence of commonality in risk exposures across banks, which supports the view that banks exhibit quite similar behavior in trading. Our empirical conclusions have some important implications for the dynamics of banks' regulatory capital. Indeed, our paper documents two sources of procyclicality in bank capital. The first one is due to the original increase in volatility while the second one arises from further volatility increases triggered by correlated risk exposures across banks, through a feedback effect.

This new framework could lead a variety of applications in the future. Implied risk exposures could, for instance, be used to study the empirical performance of the trading strategies of banks, in the spirit of the study of Agarwal et al. (2013) on hedge funds. One could also test whether some financial institutions lead their peers in terms of investment behavior. FIRE could also be used in banking supervision by complementing existing systemic risk measures (see Benoit et al. (2014) for a survey). Indeed, a situation in which a pool of large banks have a growing, common exposure to an asset class can become a serious source of concerns for banking regulators.

References

[1] Acharya, V. and Yorulmazer, T. (2007) Too many to fail - An analysis of time-inconsistency in bank closure policies, *Journal of Financial Intermediation*, 16, 1-31.

[2] Acharya, V. and Yorulmazer, T. (2008) Cash-in-the-market pricing and optimal resolution of bank failures, *Review of Financial Studies*, 21, 2705-2742.

[3] Adrian, T. and Shin, H. S. (2014) Procyclical leverage and value-at-risk, *Review of Financial Studies*, 27, 373-403.

[4] Agarwal, V., Jiang, W., Tang, Y., and Yang, B. (2013) Uncovering hedge fund skill from the portfolio holdings they hide, *Journal of Finance*, 68, 739-783.

[5] Bajgrowicz, P. and Scaillet, O. (2012) Technical trading revisited: Persistence tests, transaction costs, and false discoveries, *Journal of Financial Economics*, 106, 473-491.

[6] Bank for International Settlements (2013) Triennial central bank survey - Foreign exchange turnover in April 2013: preliminary global results, Monetary and Economic Department.

[7] Basel Committee on Banking Supervision (2011) Revisions to the Basel II market risk framework, Bank for International Settlements.

[8] Benoit, S., Colletaz, G., Hurlin, C., and Pérignon, C. (2014) A theoretical and empirical comparison of systemic risk measures, Working Paper, HEC Paris.

[9] Bhattacharyya S. and Purnanandam, A. (2011) Risk-taking by banks: What did we know and when did we know it? Working Paper, University of Michigan.

[10] Begenau, J., Piazzesi, M., and Schneider, M. (2013) Banks' risk exposures, Working Paper, Stanford University.

[11] Berkowitz, J., Christoffersen, P. F., and Pelletier, D. (2011) Evaluating value-at-risk models with desk-level data, *Management Science*, 57, 2213-2227.

[12] Berkowitz, J. and O'Brien, J. (2002) How accurate are value-at-risk models at commercial banks?, *Journal of Finance*, 57, 1093-1111.

[13] Brunnermeier, M. K. and Pedersen, L. H. (2009) Market liquidity and funding liquidity, *Review of Financial Studies*, 22, 2201-2238.

[14] Cerutti, E., Claessens, S., and McGuire, P. (2014) Systemic risk in global banking: What can available data tell us and what more data are needed?, In: Risk Topography: Systemic Risk and Macro Modeling, M. Brunnermeier and A. Krishnamurthy, Editors, University of Chicago Press.

[15] Christoffersen, P. F. (2009) Value-at-Risk Models, Handbook of Financial Time Series, Andersen, Davis, Kreiss, and Mikosch (Eds), Springer-Verlag, Berlin.

[16] Danielsson, J., Shin, H. S., and Zigrand, J. P. (2004) The impact of risk regulation on price dynamics, *Journal of Banking and Finance*, 29, 1069-1087.

[17] Ernst & Young (2012) Progress in financial services risk management: A survey of major financial institutions.

[18] Escanciano, J. C. and Olmo, J. (2011) Robust backtesting tests for value-at-risk models, *Journal of Financial Econometrics*, 9, 132-161.

[19] Farhi, E. and Tirole, J. (2012) Collective moral hazard, maturity mismatch and systemic bailouts, *American Economic Review*, 102, 60-93.

[20] Flannery, M. J. and James, C. M. (1984) The effect of interest rate changes on the common stock returns of financial institutions, *Journal of Finance*, 39, 1141-1153.

[21] Giot, P. and Laurent, S. (2003) Value-at-risk for long and short trading positions, *Journal of Applied Econometrics*, 18, 641-664.

[22] Gordy, M. (2003) A risk-factor model foundation for rating-based bank capital rules, *Journal of Financial Intermediation*, 12, 199-232.

[23] Gourieroux, C. and Zakoian, J. M. (2013) Estimation adjusted VaR, *Econometric Theory*, 29, 735-770.

[24] Greene, W.H. (2012) *Econometric Analysis*, Prentice Hall, 7th Edition.

[25] Hansen, B. E. (1994) Autoregressive conditional density estimation, *International Economic Review*, 35, 705-730.

[26] Harvey, C. and Siddique, A. (1999) Autoregressive conditional skewness, *Journal of Financial and Quantitative Analysis*, 34, 465-487.

[27] Harvey, C. and Siddique, A. (2000) Conditional skewness in asset pricing tests, *Journal of Finance*, 55, 1263-1295.

[28] Herskovic, B., Kelly, B., Hanno, L., and Van Nieuwerburgh, S. V. (2014) The common factor in idiosyncratic volatility: Quantitative asset pricing implications, Working Paper, University of Chicago.

[29] Hirshleifer, D., Subrahmanyam, A., and Titman, S. (1994) Security analysis and trading patterns when some investors receive information before others, *Journal of Finance*, 49, 1665-1698.

[30] Landier, A., Thesmar, D., and Sraer, D. (2013) Bank exposure to interest-rate risk and the transmission of monetary policy, Working Paper, Princeton University.

[31] Jorion, P. (2006) Bank trading risk and systemic risk, In: The Risks of Financial Institutions, M. Carey and R. M. Stulz, Editors, University of Chicago Press.

[32] Jorion, P. (2007) Value at Risk: The New Benchmark for Managing Financial Risk. McGraw-Hill, 3rd Edition.

[33] Merrill, C., Nadauld, T., Stulz, R. M., and Sherlund, S. M. (2013) Why did financial institutions sell RMBS at fire sale prices during the financial crisis?, Working Paper, Ohio State University.

[34] Morris, S. and Shin, H. S. (1999) Risk management with interdependent choice, *Oxford Review of Economic Policy*, 15, 52-62.

[35] O'Brien, J. and Berkowitz, J. (2006) Estimating bank trading risk: A factor model approach, In: The Risks of Financial Institutions, M. Carey and R. M. Stulz, Editors, University of Chicago Press.

[36] Pavlova, A. and Rigobon, R. (2008) The role of portfolio constraints in the international propagation of schocks, *Review of Economic Studies*, 75, 1215-1256.

[37] Pérignon, C. and Smith, D. R. (2010) Diversification and value-at-risk, *Journal of Banking and Finance*, 34, 55-66.

[38] Persaud, A. (2000) Sending the herd off the cliff edge: The disturbing interaction between herding and market-sensitive risk management practices, *Journal of Risk Finance*, 2, 59-65.

[39] Rossignolo, A. F., Fethi, M. D., and Shaban, M. (2013) Market crises and Basel capital requirements: Could Basel III have been different? Evidence from Portugal, Ireland, Greece and Spain (PIGS), *Journal of Banking and Finance*, 37, 1323-1339.

[40] Risk (2010) What does VAR mean in 2010? *Risk Magazine*, April 2010, 24-28.

[41] Taylor, J. W. (2005) Generating volatility forecasts from value at risk estimates, *Management Science*, 51, 712-725.

Table 1: Change in Factor VaR and Factor Volatility between 2008 and 2009

$\%\Delta VaR$	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	**54**	**137**	**355**	**442**
BNP Paribas	-30	-35	-48	**25**
Citigroup	-18	-40	-62	**20**
Credit Agricole	-56	-73	-57	**200**
Credit Suisse	**33**	**36**	-56	**17**
Deutsche Bank	**7**	-15	-37	**10**
Goldman Sachs	**161**	-46	-42	0
JPMorgan Chase	-7	-51	-74	-12
Morgan Stanley	0	**45**	**86**	**4**
UBS	**11**	-26	-56	-40
$\%\Delta Volatility$	-46	-43	-39	-59

Notes: The source for the VaR figures are the EDGAR database for US banks and firms' websites for international banks. We use a specific implied volatility index for each risk factor. The volatility on the equity market is measured by the Chicago Board Options Exchange VIX index. The volatility on the fixed income market is measured by the Merrill Lynch MOVE index, which tracks the volatility of Treasury bond prices using implied volatility from 30-day options. The volatility on the foreign exchange market is measured by the Deutsche Bank CVIX index, an average 3-month implied volatility for all the major currency pairs. The volatility on the commodity market is measured by the Chicago Board Options Exchange OVX index, a measure of 30-day implied volatility in West Texas Intermediate crude oil prices. Bold figures denote positive percentage changes. All sample banks report end-of-quarter daily VaR except Bank of America and BNP Paribas that report average daily VaR for each quarter. Values are expressed in percentage points.

Table 2: Changes in Equity Risk Exposure for Goldman Sachs

End of Quarter	$\%\Delta VaR_t$	$\%\Delta VIX_t$	$\%\Delta E_t$	Excerpts taken from 10-Q forms
2013Q3	43	-12	61	"increases in the equity prices [...] categories principally due to increased exposures", p.177
2013Q2	30	-26	76	"increases in the equity prices [...] categories, principally due to increased exposures", p.179
2013Q1	3	-26	40	[n/a]
2012Q3	-13	-47	65	[n/a]
2012Q2	-34	15	-43	"decreases in the [...] equity prices categories, principally due to reduced exposures", p.165
2012Q1	-41	-2	-39	"decreases in the equity prices [...] categories, principally due to reduced exposures", p.155
2011Q3	-59	26	-67	"decreases in the equity prices category, principally due to reduced exposures", p.160
2011Q2	-43	-34	-13	"decreases across most risk categories, primarily due to reduced exposures", p.156
2011Q1	-44	-8	-40	"The decreases in the equity prices [...] categories were primarily due to reduced exposures", p.138
2010Q3	-22	-5	-18	[n/a]
2010Q2	2	-20	27	[n/a]
2010Q1	132	-55	417	"The increase in equity prices was primarily due to increased equity exposures", p.119
2009Q3	10	14	-3	[n/a]
2009Q2	-24	48	-49	[n/a]
2009Q1	-57	85	-77	"The decrease in equity prices was primarily due to lower levels of exposures", p.124
2008Q3	-31	16	-41	"The decrease in equity prices was principally due to position reductions", p.105
2008Q2	-22	61	-51	"decrease in exposures to equity prices", p.101
2008Q1	-7	120	-58	[n/a]
2007Q3	59	27	25	"primarily reflecting increased levels of exposure and volatility in [...] equity prices", p.86
2007Q2	22	9	12	"primarily due to increased levels of exposure to [...] equity prices", p.85
2007Q1	39	-7	50	"primarily due to increased levels of exposure to equity prices", p.79
2006Q3	53	26	21	[n/a]
2006Q2	219	-8	248	"The increase was primarily due to higher levels of exposure to equity prices", p.90
2006Q1	138	-5	151	"The increase was primarily due to higher levels of exposure to equity prices", p.86
2005Q3	29	-24	71	"The increase was primarily due to higher levels of exposure to equity prices", p.79
2005Q2	-30	-19	-13	"The decrease was primarily due to lower levels of exposure to equity prices", p.75
2005Q1	-22	-23	2	[n/a]
2004Q3	29	-19	60	"The increase was primarily due to higher levels of exposure to equity prices", p.65
2004Q2	54	-32	126	"The increase was primarily due to higher levels of exposure to equity prices", p.65
2004Q1	19	-44	113	[n/a]

Notes: This table presents the 1-year percentage changes in equity VaR (average daily 95% VaR over the quarter), VIX, and equity risk exposures for Goldman Sachs between 2004Q1 and 2013Q3 (30 quarters). The VaR figures are from the firm's 10-Q forms, the VIX is from the CBOE website, and the changes in risk exposures are computed using the FIRE methodology. The right column of the table contains excerpts taken from the 10-Q forms of Goldman Sachs. [n/a] indicates that the 10-Q form contains no specific sentences about changes in equity risk exposures. Values are expressed in percentage points.

Table 3: Monte Carlo Experiments

Panel A: Design of the Monte Carlo Experiments				
	Exp. 1	**Exp. 2**	**Exp. 3**	**Exp. 4**
DGP of the return	Garch(1,1)	Garch(1,1)	Garch(1,1)	Garch(1,1)
Bank VaR Model	RiskMetrics	RiskMetrics	HS	HS
FIRE Model	RiskMetrics	Garch(1,1)	HV	Garch(1,1)
Panel B: Experiment 1 - Model Risk				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	100 (100)	0.0000	0.0000	1.000
1,000	100 (100)	0.0000	0.0000	1.000
2,000	100 (100)	0.0000	0.0000	1.000
Panel C: Experiment 2 - Estimation Risk				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	99.18 (99.63)	0.0065	11.8779	0.9924
1,000	99.38 (99.83)	0.0054	9.9131	0.9948
2,000	99.51 (99.91)	0.0048	8.7629	0.9960
Panel D: Experiment 3 - Model Risk				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	99.29 (99.33)	0.0058	10.6340	0.9925
1,000	99.29 (99.33)	0.0058	10.6336	0.9923
2,000	99.29 (99.33)	0.0058	10.6332	0.9923
Panel E: Experiment 4 - Model and Estimation Risks				
Sample Size	**Matching Signs (%)**	**MAE**	**MAPE (%)**	$\mathbf{R}^2$
250	92.01 (91.71)	0.0306	56.1063	0.8978
1,000	92.03 (91.57)	0.0305	55.8513	0.8987
2,000	92.05 (91.49)	0.0304	55.6789	0.8995

Notes: This table presents the design and the results of the Monte Carlo simulations. In the four experiments, we vary (1) the data generating process (DGP) of the return, (2) the bank VaR model, and (3) the FIRE model used to extract the conditional volatility. HV denotes historical volatility and HS historical simulation. For each experiment, we report the percentage of positive and negative (in parentheses) matching signs between the true change in risk exposure and the implied change in risk exposure extracted with the FIRE methodology. We also display the average of the Moving Absolute Error (MAE) and the Moving Absolute Percentage Error (MAPE) between the changes in the true risk exposure and the implied risk exposure extracted with the FIRE methodology. Finally, we report the average R^2 statistic obtained by regressing the true position changes on a constant and the implied risk exposure. In each experiment, we vary the sample size from 250 to 2,000 observations and we use 100,000 simulations.

Table 4: Commonality in Volatility Within an Asset Class

	Equity	Interest Rate	Foreign Exchange	Commodity
Panel A: Yearly Volatility Estimates				
Loading (average)	1.006	1.007	1.000	1.000
Intercept (average)	0.028	0.031	0.000	0.000
R^2 (average univariate)	0.668	0.451	0.581	0.341
R^2 (pooled)	0.631	0.416	0.326	0.345
Observations	6,659	2,004	670	315
Number of assets	451	146	45	21
Panel B: Quarterly Volatility Estimates				
	Equity	Interest Rate	Foreign Exchange	Commodity
Loading (average)	1.007	1.010	1.000	1.000
Intercept (average)	0.035	0.037	0.003	0.000
R^2 (average univariate)	0.642	0.509	0.592	0.333
R^2 (pooled)	0.612	0.463	0.354	0.309
Observations	27,347	8,353	2,766	1,302
Number of assets	485	148	45	21
Panel C: Monthly Volatility Estimates				
	Equity	Interest Rate	Foreign Exchange	Commodity
Loading (average)	1.011	1.008	1.000	1.000
Intercept (average)	0.056	0.034	0.003	0.000
R^2 (average univariate)	0.563	0.499	0.522	0.295
R^2 (pooled)	0.548	0.446	0.339	0.267
Observations	82,373	25,051	8,297	3,906
Number of assets	498	148	45	21

Notes: This table presents the estimated coefficients obtained by regressing the asset-level volatility (in log) on the average volatility (in log) within the asset class. In each panel, the average volatility is defined as the equally-weighted average of securities' volatilities in a given time period: one year in Panel A, one quarter in Panel B, and one month in Panel C. The volatility measures are estimated using the historical standard-deviation of the daily returns, which are available for the period January 1, 1999 to June 20, 2014 (respectively, end of 2013 for equities). Cross-sectional averages of both loading and intercept estimates and R^2 are reported for each asset class. The pooled factor model R^2 comes from a panel regression with securities' fixed-effects and a common volatility (within estimator). The table also reports the number of observations in the pooled model as well as the number of securities used in each asset class.

Table 5: **Correlation in Factor VaR across Banks**

Average Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	-15	14	-9	-11
BNP Paribas	49	49	4	32
Citigroup	53	47	23	36
Credit Agricole	56	57	18	8
Credit Suisse	54	49	-1	34
Deutsche Bank	59	63	3	-21
Goldman Sachs	49	55	24	35
JPMorgan Chase	12	53	22	25
Morgan Stanley	32	31	7	27
UBS	56	15	11	26
Sample Average	*41*	*43*	*10*	*19*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	39	53	50	45
BNP Paribas	50	64	51	36
Citigroup	50	52	50	53
Credit Agricole	40	62	32	24
Credit Suisse	50	55	54	50
Deutsche Bank	52	59	52	42
Goldman Sachs	44	58	62	54
JPMorgan Chase	46	63	52	49
Morgan Stanley	50	55	46	46
UBS	50	52	54	37
Sample Average	*47*	*57*	*50*	*44*

Notes: The upper panel of the table presents the average correlation between the quarterly VaR of a bank and the quarterly VaR of all other sample banks for each risk factor between 2007Q3 and 2013Q3 (25 observations per bank). The lower panel reports the frequency with which the quarterly VaR of banks i and j move in the same direction (+/+ or -/-). For each bank, we compute the percentage of matching signs between the ΔVaR_{ift} of that bank and the ΔVaR_{jft} of all other sample banks, $j \neq i$. Values are expressed in percentage points.

Table 6: Correlation between Factor VaR and Factor Volatility

Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	12	-9	-5	-12
BNP Paribas	52	73	43	15
Citigroup	44	49	64	20
Credit Agricole	33	79	53	10
Credit Suisse	21	52	-1	36
Deutsche Bank	32	66	37	-6
Goldman Sachs	-2	77	43	51
JPMorgan Chase	65	68	59	40
Morgan Stanley	-13	8	-8	-8
UBS	26	68	15	17
Sample Average	*27*	*53*	*30*	*16*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	52	40	44	48
BNP Paribas	44	60	56	36
Citigroup	76	40	36	52
Credit Agricole	44	48	36	28
Credit Suisse	48	56	48	40
Deutsche Bank	44	48	56	44
Goldman Sachs	48	64	52	60
JPMorgan Chase	48	68	48	44
Morgan Stanley	32	52	28	48
UBS	44	60	32	36
Sample Average	*48*	*54*	*44*	*44*

Notes: The upper panel of this table presents the correlation between the quarterly VaR of a bank and the factor volatility between 2007Q3 and 2013Q3 (25 observations per bank). The lower panel reports the frequency with which the quarterly VaR of a given bank move in the same direction as the factor volatility (+/+ or -/-). For each bank, we compute the percentage of matching signs between its ΔVaR_{ift} and the $\Delta \sigma_{ft}$. Values are expressed in percentage points.

Table 7: Bank Risk Exposures and Volatility

Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	-59	-59	-33	-34
BNP Paribas	-50	-35	-27	-54
Citigroup	-34	-46	-13	-55
Credit Agricole	-35	-50	-3	-41
Credit Suisse	-59	-70	-26	-67
Deutsche Bank	-58	-78	-28	-61
Goldman Sachs	-69	-59	-22	-47
JPMorgan Chase	-21	-44	8	-79
Morgan Stanley	-77	-68	-70	-82
UBS	-65	-47	-39	-43
Sample Average	*-53*	*-56*	*-25*	*-56*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	12	28	20	24
BNP Paribas	32	36	36	28
Citigroup	56	16	20	36
Credit Agricole	32	36	36	20
Credit Suisse	24	32	32	20
Deutsche Bank	24	24	32	24
Goldman Sachs	24	40	28	28
JPMorgan Chase	40	44	40	20
Morgan Stanley	12	28	20	16
UBS	28	24	24	20
Sample Average	*28*	*31*	*29*	*24*

Notes: The upper panel of this table presents the correlation between the percentage change in the quarterly risk exposure of a bank and the percentage change in quarterly factor volatility between 2007Q3 and 2013Q3 (25 observations per bank). The lower panel reports the frequency with which the quarterly risk exposure of a given bank move in the same direction as the factor volatility (+/+ or -/-). For each bank, we compute the percentage of matching signs between its ΔE_{ift} and the $\Delta \sigma_{ft}$. Values are expressed in percentage points.

Table 8: Commonality in Bank Risk Exposures

Average Correlation	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	30	35	-2	26
BNP Paribas	42	19	7	23
Citigroup	15	19	8	43
Credit Agricole	21	40	5	29
Credit Suisse	38	42	13	43
Deutsche Bank	47	44	9	36
Goldman Sachs	50	38	26	32
JPMorgan Chase	18	37	8	46
Morgan Stanley	49	33	12	40
UBS	48	36	24	23
Sample Average	*36*	*34*	*11*	*34*
% of Matching Signs	Equity	Interest Rate	Foreign Exchange	Commodity
Bank of America	64	59	52	64
BNP Paribas	68	52	55	55
Citigroup	58	63	62	65
Credit Agricole	56	63	57	65
Credit Suisse	66	63	56	71
Deutsche Bank	69	66	60	63
Goldman Sachs	68	63	62	68
JPMorgan Chase	64	66	55	68
Morgan Stanley	68	65	60	70
UBS	67	64	64	67
Sample Average	*65*	*62*	*58*	*66*

Notes: The upper panel of the table presents the average correlation between the percentage change in risk exposures of a bank, $\%\Delta E_{ift}$, and the quarterly changes in risk exposures of all other sample banks, $\%\Delta E_{jft}$, $j \neq i$, between 2007Q3 and 2013Q3 (25 observations per bank). The changes in risk exposures are obtained using the FIRE methodology. The lower panel reports the frequency with which the quarterly change in risk exposures of banks i and j move in the same direction (+/+ or -/-). Values are expressed in percentage points.

Table 9: Panel Regression Analysis of Changes in Risk Exposures

	Equity		Interest Rate		Foreign Exchange		Commodity		All Factors	
	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{it}$	$\%\Delta E_{it}$
$\overline{\%\Delta E_{jft}}$	0.450***	0.323**	0.475***	0.479***	0.367*	0.360*	0.375*	0.388*	0.438***	0.435***
	(0.122)	(0.130)	(0.086)	(0.085)	(0.171)	(0.178)	(0.173)	(0.207)	(0.064)	(0.065)
$\%\Delta\sigma_{ft}$	-0.370***	-0.304***	-0.479***	-0.490***	-0.420**	-0.310	-0.652***	-0.661***	-0.437***	-0.433***
	(0.061)	(0.056)	(0.075)	(0.090)	(0.184)	(0.356)	(0.153)	(0.146)	(0.060)	(0.061)
R_{ft}		0.702		-0.013		-0.659		0.095		0.027
		(0.390)		(0.079)		(1.889)		(0.274)		(0.075)
CDS_{it}		0.0391		-0.0232		0.0513		-0.0510		0.0001
		(0.0005)		(0.0002)		(0.0008)		(0.0003)		(0.0002)
RoE_{it}		-0.0016		0.0049		-0.0019		0.0010		0.0011
		(0.0028)		(0.0040)		(0.0027)		(0.0021)		(0.0024)
Observations	250	250	250	250	250	250	250	250	1,000	1,000
R^2	0.284	0.293	0.339	0.348	0.081	0.088	0.259	0.266	0.225	0.226

Notes: This table presents the estimated coefficients and robust standard errors (in parentheses) for several regressions of the percentage changes in risk exposures for the 10 sample banks using an OLS panel regression with bank fixed effects in single factor regressions, columns (1)-(8), and with bank and factor fixed effects in the regressions aggregating all factors, columns (9)-(10). The dependent variable is the percentage change in risk exposure ($\%\Delta E_{ift}$). ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively. R_{it} denotes the factor return over the quarter, CDS_{it} denotes the CDS of bank i at the beginning of the quarter, and RoE_{it} denotes the return on equity of bank i over the quarter. Each regression is run separately over an estimation period covering 2007Q3-2013Q3.

Table 10: Robustness Check

	Equity	Interest Rate	Foreign Exchange	Commodity	All Factors
	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$	$\%\Delta E_{ift}$
	Panel A: Value-Weighted Commonality Proxy				
$\overline{\%\Delta E_{jft}}$	0.275**	0.389***	0.321**	0.383*	0.349***
	(0.089)	(0.079)	(0.128)	(0.177)	(0.059)
$\%\Delta\sigma_{ft}$	-0.472***	-0.508***	-0.507**	-0.652***	-0.501***
	(0.068)	(0.078)	(0.159)	(0.166)	(0.057)
	Panel B: First Principal Component as Commonality Proxy				
$\overline{\%\Delta E_{jft}}$	0.234***	0.225***	0.204**	0.181*	0.211***
	(0.067)	(0.039)	(0.080)	(0.099)	(0.016)
$\%\Delta\sigma_{ft}$	-0.197	-0.332***	-0.321	-0.503*	-0.300***
	(0.127)	(0.072)	(0.184)	(0.255)	(0.053)
	Panel C: Historical Volatility				
$\overline{\%\Delta E_{jft}}$	0.749***	0.630***	0.567***	0.313	0.619***
	(0.113)	(0.172)	(0.016)	(0.181)	(0.056)
$\%\Delta\sigma_{ft}$	-0.206**	-0.292**	-0.292*	-0.638***	-0.300***
	(0.070)	(0.109)	(0.142)	(0.111)	(0.053)
	Panel D: Controlling for Factor Returns				
	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$	$\%\Delta E_{ift} - R_{ft}$
$\overline{\%\Delta E_{jft} - R_{ft}}$	0.384**	0.885***	0.378**	0.400*	0.663***
	(0.142)	(0.067)	(0.164)	(0.200)	(0.052)
$\%\Delta\sigma_{ft}$	-0.303***	-0.284**	-0.467**	-0.481***	-0.261***
	(0.055)	(0.091)	(0.192)	(0.130)	(0.053)

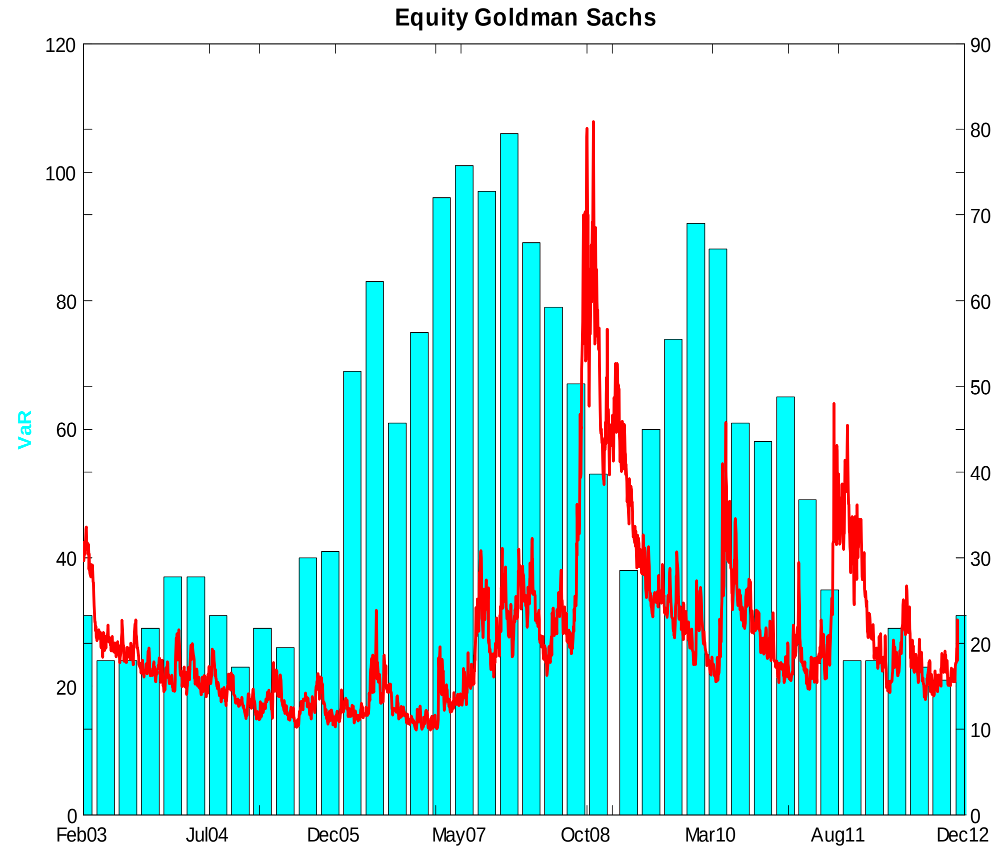
Notes: This table presents the estimated coefficients and robust standard errors (in parentheses) for several regressions of the percentage changes in risk exposures for the 10 sample banks using an OLS panel regression with bank fixed effects in single factor regressions, columns (1)-(8), and with bank and factor fixed effects in the regressions aggregating all factors, columns (9)-(10). The dependent variable is the percentage change in risk exposure ($\%\Delta E_{ift}$ or $\%\Delta E_{ift} - R_{ft}$). ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively. Each regression is run separately over an estimation period covering 2007Q3-2013Q3.

Table 11: Subsample Analysis

	Equity	Interest Rate	Foreign Exchange	Commodity
Episode of Increase in Volatility (2007Q3-2008Q4)				
$\%\Delta Volatility$	26	23	27	22
$\%\Delta VaR$	1	26	24	3
$\%\Delta E$	-15	9	-0.1	-13
Corr($\%\Delta E_{ift}, \%\Delta E_{jft}$)	19	28	5	46
% of Matching Signs	70	52	70	69
Episode of Reduction in Volatility (2009Q1-2010Q1)				
$\%\Delta Volatility$	-15	-12	-11	-18
$\%\Delta VaR$	10	-5	14	13
$\%\Delta E$	31	16	30	41
Corr($\%\Delta E_{ift}, \%\Delta E_{jft}$)	3	58	24	23
% of Matching Signs	49	73	63	62

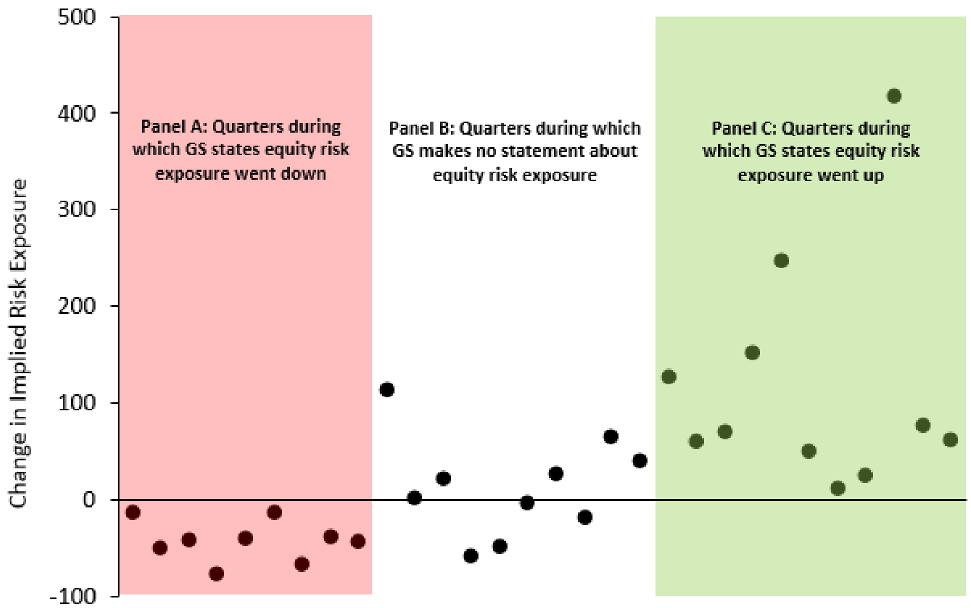
Notes: In this table, we contrast two subsamples. The upper (lower) panel presents the results for an episode of increase (decrease) in market volatility. In each panel, we present the average quarterly percentage change in the factor volatility index ($\%\Delta Volatility$), the average quarterly percentage change in factor VaR ($\%\Delta VaR$), the average quarterly percentage change in risk exposure ($\%\Delta E$), and the average correlation between the percentage change in risk exposures of a bank, $\%\Delta E_{ift}$, and quarterly changes risk exposure of the nine other banks, $\%\Delta E_{jft}$, $j \neq i$. Values are expressed in percentage points.

Figure 1: FIRE Analysis of Goldman Sachs' Equity VaR



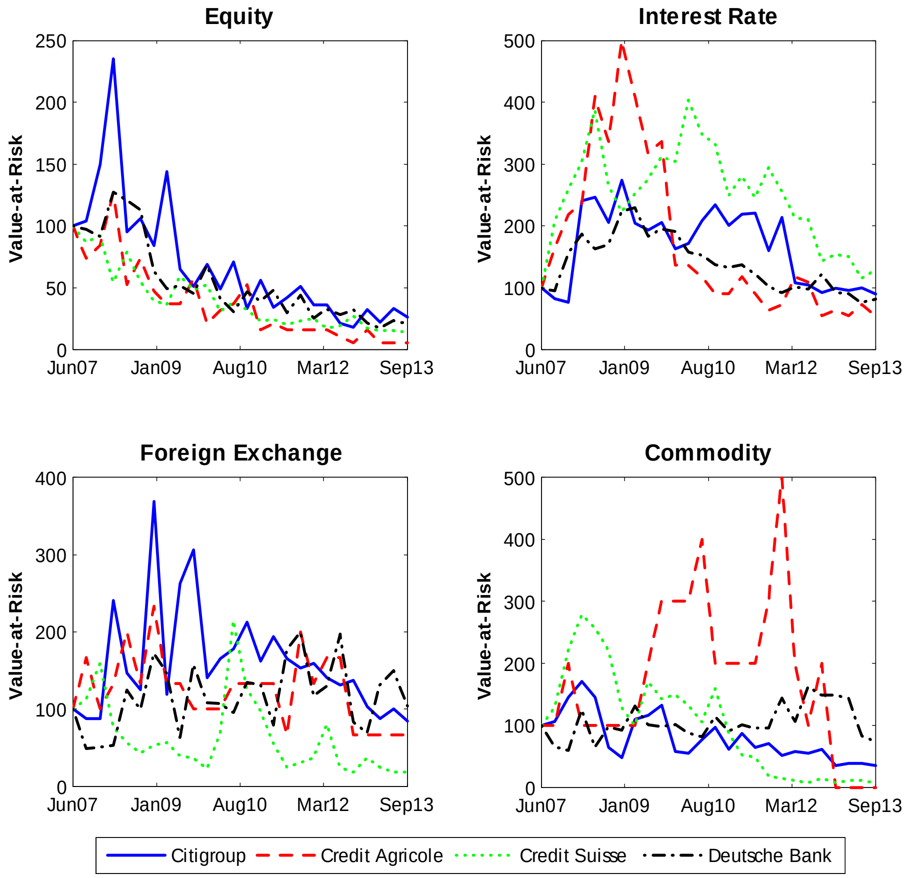
Notes: This figure displays the quarterly, average, 95%-confidence level, one-day ahead equity VaR of Goldman Sachs (grey bars) and VIX index (red line). The sample period covers 2003Q1-2013Q4, the VaR figures are in USD millions, and the VIX index is in percentage points. Note that the gap in VaR data immediately after November 2008 is due to the fact that the company changed its fiscal year-end from November to December.

Figure 2: Empirical Performance of the FIRE Methodology



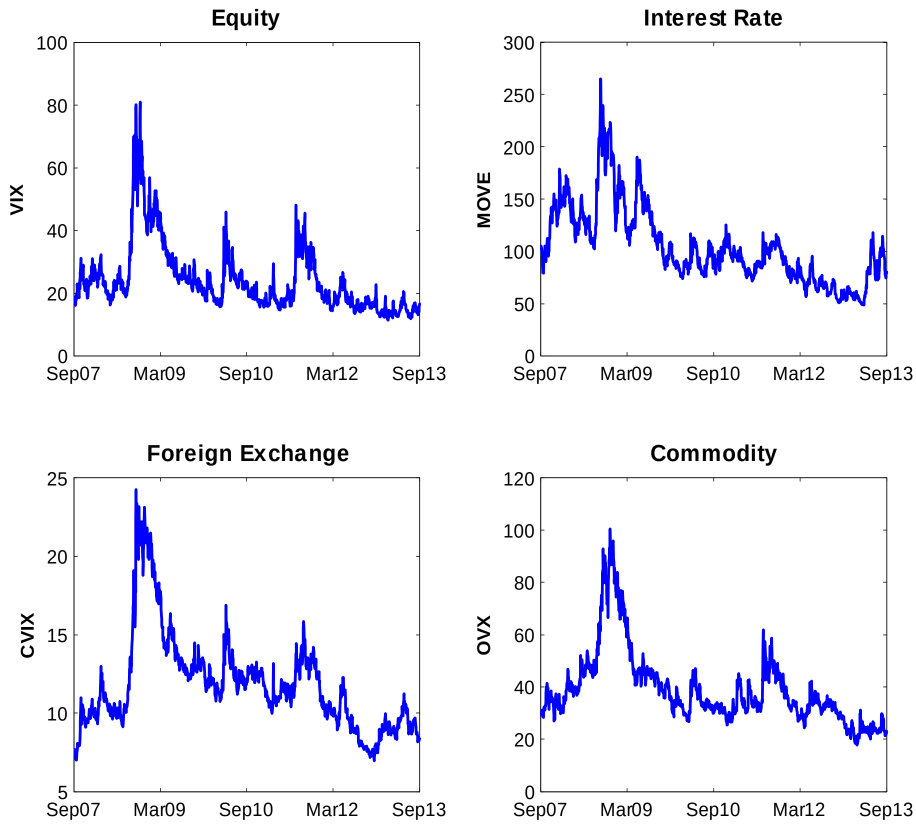
Notes: This figure displays the percentage change in implied equity risk exposure of Goldman Sachs (GS) between 2003Q1 and 2013Q3. For each quarter Q in year Y, we extract the change in equity risk exposure between quarter Q in year Y and quarter Q in year Y-1 using the FIRE methodology. The 30 quarters have been divided into three subsamples according to statements made by the firm in its 10-Q reports regarding its actual change in risk exposures. There are nine quarters during which the firm stated that its equity risk exposure did go down (Panel A), ten quarters during which the firm made no statements about its change in equity risk exposure (Panel B), and eleven quarters during which the firm stated that its equity risk exposure did go up (Panel C). In each panel, the quarters are ranked chronologically. See Table 2 for a list of the quarters in each panel.

Figure 3: Evolution of the Factor VaR



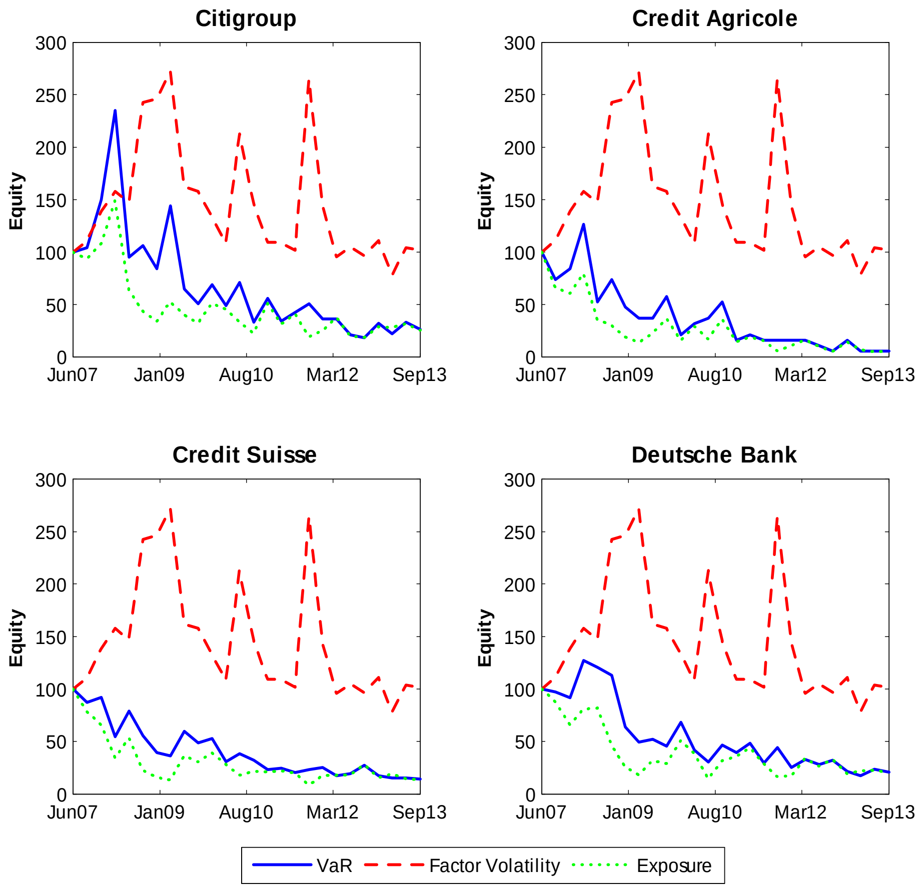
Notes: This figure displays the one-day ahead 99% factor VaR of Citigroup, Credit Agricole, Credit Suisse, and Deutsche Bank for four risk factors (equity, interest rate, foreign exchange, and commodity). All values are set to 100 in 2007Q2.

Figure 4: Evolution of the Factor Volatility Indices



Notes: This figure displays the daily factor volatility for each risk factor (equity, interest rate, foreign exchange, and commodity) from 2007Q2 to 2013Q3. The volatility on the equity market is measured by the Chicago Board Options Exchange VIX index. The volatility on the fixed income market is measured by the Merrill Lynch MOVE index, which tracks the volatility of Treasury bond prices using implied volatility from 30-day options. The volatility on the foreign exchange market is measured by the Deutsche Bank CVIX index, an average 3-month implied volatility for all the major currency pairs. The volatility on the commodity market is measured by the Chicago Board Options Exchange OVX index, a measure of 30-day implied volatility in West Texas Intermediate crude oil prices.

Figure 5: Equity VaR and its Driving Forces



Notes: This figure displays the equity VaR (blue solid line), equity volatility (VIX index, red dashed line), and the implied risk exposure (green dotted line) extracted using the FIRE methodology with factor volatility indices. All values are set to 100 in 2007Q2.

Appendix: VaR Data

Bank	Horizon and Confidence Level	Type of VaR Disclosed	Fiscal Year-End
Bank of America	1-day 99% VaR from 2007Q2 to 2013Q3	Average over the quarter	
BNP Paribas	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter from 2007Q2 to 2008Q1 Average over the quarter from 2008Q1 to 2013Q3	
Citigroup	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter	
Credit Agricole	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter	
Credit Suisse	1-day 99% VaR from 2007Q2 to 2012Q3 1-day 98% VaR from 2011Q1 to 2013Q3	End of quarter	
Deutsche Bank	1-day 99% VaR from 2007Q2 to 2013Q3	End of quarter	
Goldman Sachs	1-day 95% VaR from 2003Q1 to 2013Q3	End of quarter Average over the quarter Year end Average over the year	November until 2008, then December
JPMorgan Chase	1-day 99% VaR from 2007Q2 to 2009Q4 1-day 95% VaR from 2009Q1 to 2013Q3	End of quarter	
Morgan Stanley	1-day 95% VaR from 2007Q2 to 2013Q3	End of quarter	November until 2008, then December
UBS	10-day 99% VaR from 2007Q2 to 2009Q4 1-day 95% VaR from 2008Q4 to 2013Q3	End of quarter	

Notes: We transform 10-day VaRs into 1-day VaRs by dividing the former by $\sqrt{10}$ (square root of time rule). We also transform 95% and 98% VaRs into 99% VaRs by multiplying the former VaRs respectively by 1.4143 and 1.1327, which are equal to $\Phi^{-1}(0.99)/\Phi^{-1}(0.95)$ and $\Phi^{-1}(0.99)/\Phi^{-1}(0.98)$ (normal distribution).